Unsupervised Meta-Learning for Few-Shot Image Classification

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Contributions

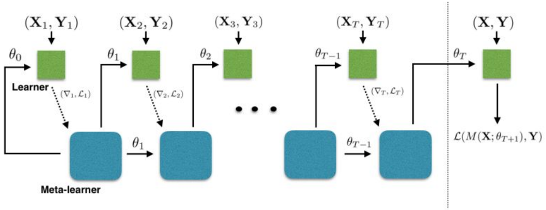
- Unsupervised meta-learning algorithm by
  - Generating synthetic tasks
  - Studying the relationship between validation set and train set of a task
- Results evaluated on different dominas:
  - Few-shot learning benchmarks
  - Videos
  - Face Recognition

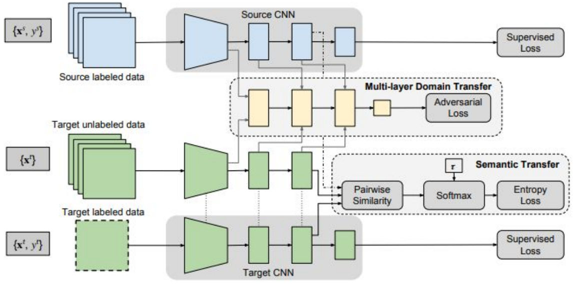
Background

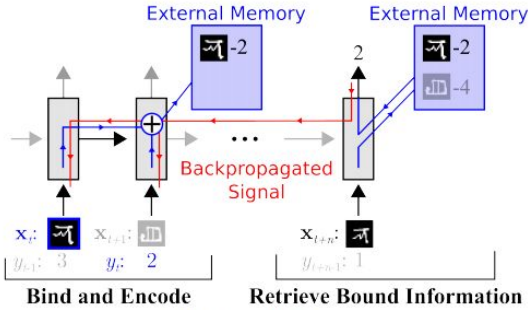
- Meta-learning
  - Look at a lot of tasks:
    - $T_1, T_2, \ldots, T_n$
    - Update parameters such that we can learn them with fewer examples and faster
  - Target learning phase:
    - Unseen task T_{n+1}

Few-shot learning approaches

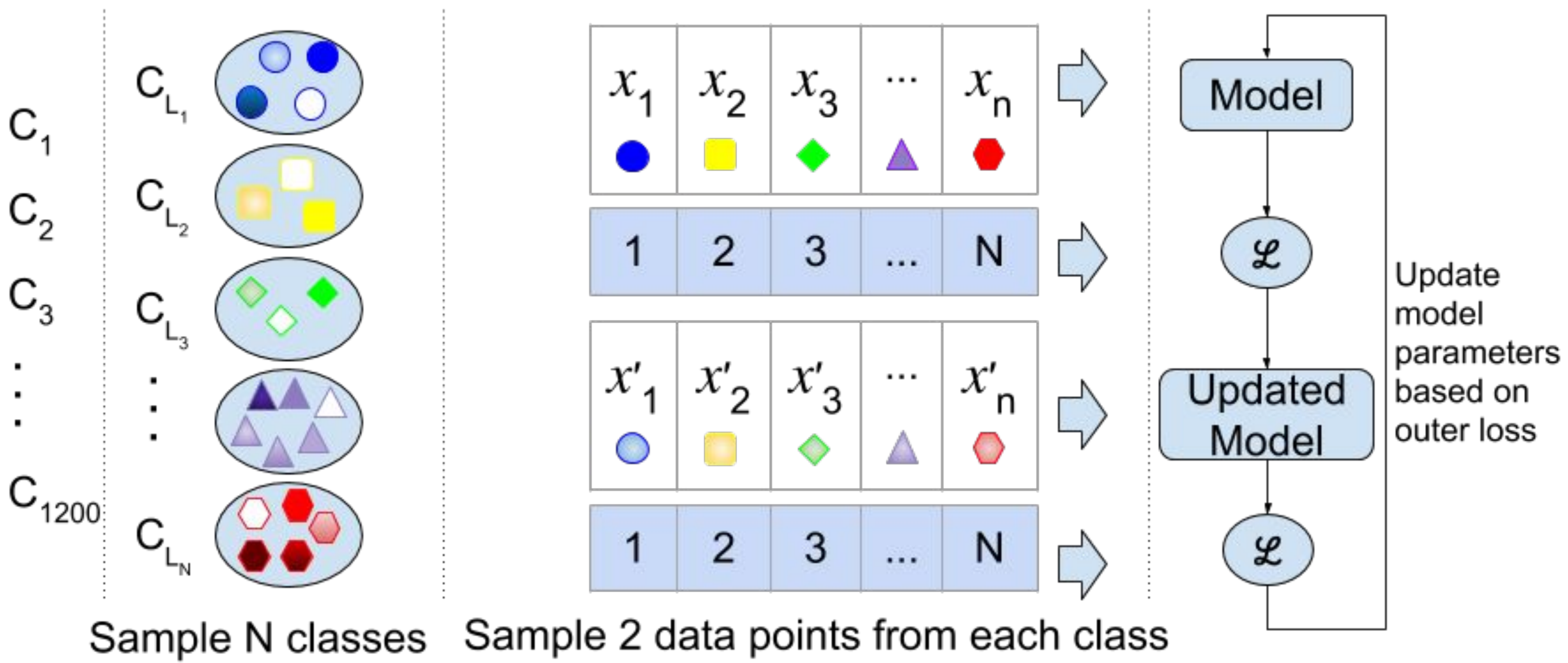
- Model-agnostic meta-learning.
- Label efficient learning of transferable representations across domains and tasks.
- Memory augmented neural networks.
- Optimization as a model.
- etc.







Preparing data for meta-learning (1-shot)



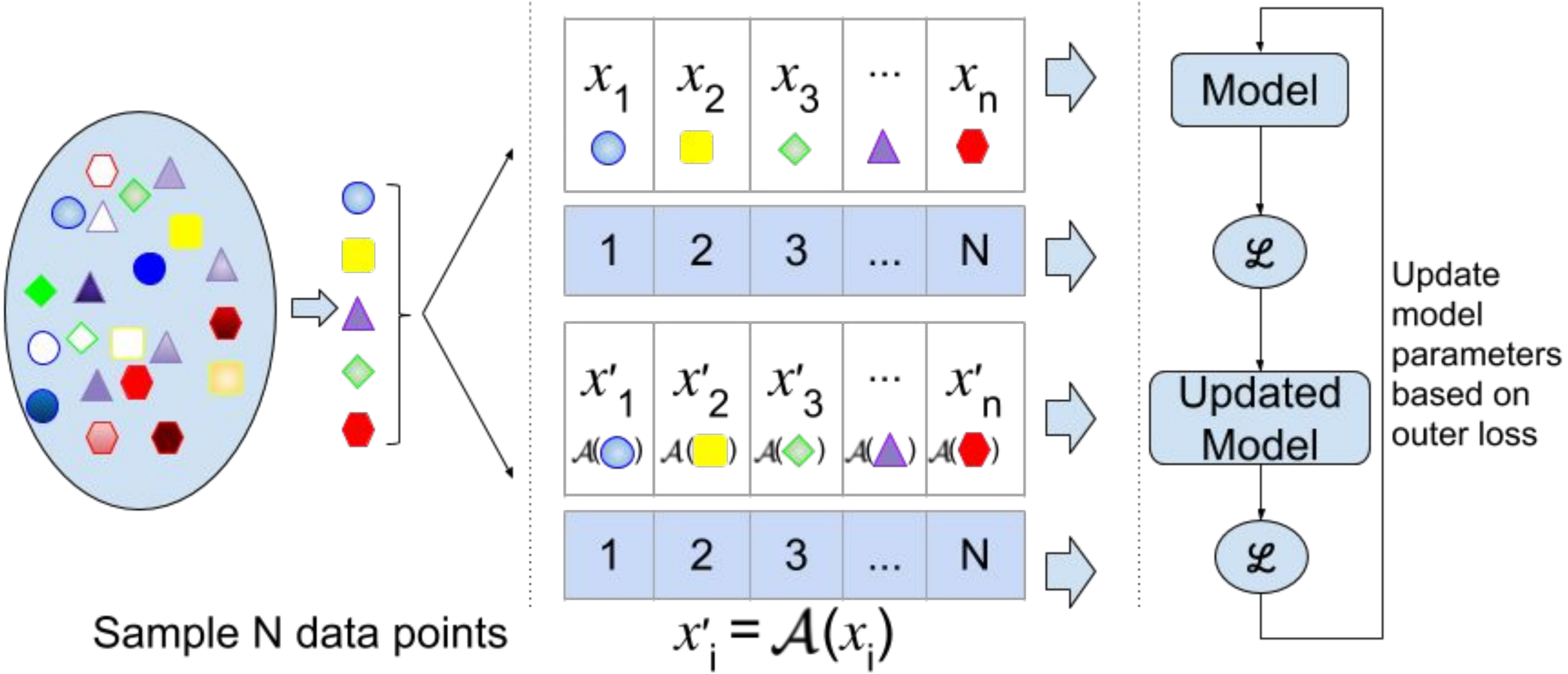
Intuition

- Meta Learning
  - Tasks
  - Tasks are created with supervision

Photo by Tanaphong Toochinda on Unsplash

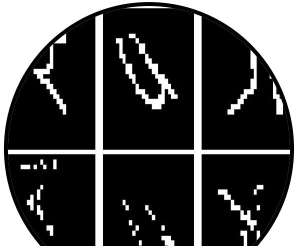
- Unsupervised meta-learning
- Can we generate tasks in an unsupervised manner?

Unsupervised Meta-learning with Tasks constructed by Random sampling and Augmentation (UMTRA)



Results

Few-shot learning benchmarks



		Omniglot				Mini-Imagenet			
Algorithm (N, K)	**Clustering**	**(5,1)**	**(5,5)**	**(20,1)**	**(20,5)**	**(5,1)**	**(5,5)**	**(5,20)**	**(5,50)**
Training from scratch	N/A	52.50	74.78	24.91	47.62	27.59	38.48	51.53	59.63
k_{nn}-nearest neighbors	BiGAN	49.55	68.06	27.37	46.70	25.56	31.10	37.31	43.60
linear classifier	BiGAN	48.28	68.72	27.80	45.82	27.08	33.91	44.00	50.41
MLP with dropout	BiGAN	40.54	62.56	19.92	40.71	22.91	29.06	40.06	48.36
cluster matching	BiGAN	43.96	58.62	21.54	31.06	24.63	29.49	33.89	36.13
CACTUs-MAML	BiGAN	58.18	78.66	35.56	58.62	36.24	51.28	61.33	66.91
CACTUs-ProtoNets	BiGAN	54.74	71.69	33.40	50.62	36.62	50.16	59.56	63.27
k_{nn}-nearest neighbors	ACAI / DC	57.46	81.16	39.73	66.38	28.90	42.25	56.44	63.90
linear classifier	ACAI / DC	61.08	81.82	43.20	66.33	29.44	39.79	56.19	65.28
MLP with dropout	ACAI / DC	51.95	77.20	30.65	58.62	29.03	39.67	52.71	60.95
cluster matching	ACAI / DC	54.94	71.09	32.19	45.93	22.20	23.50	24.97	26.87
CACTUs-MAML	ACAI / DC	68.84	87.78	48.09	73.36	39.90	**53.97**	**63.84**	**69.64**
CACTUs-ProtoNets	ACAI / DC	68.12	83.58	47.75	66.27	39.18	53.36	61.54	63.55
UMTRA (ours)	N/A	**83.80**	**95.43**	**74.25**	**92.12**	**39.93**	50.73	61.11	67.15
MAML (Supervised)	N/A	94.46	98.83	84.60	96.29	46.81	62.13	71.03	75.54
ProtoNets (Supervised)	N/A	98.35	99.58	95.31	98.81	46.56	62.29	70.05	72.04

UCF-101 results

Algorithm	Test Accuracy / F1-Score
Training from scratch	29.30 / 20.48
Pre-trained on Kinetics	45.51 / 42.49
UMTRA on unlabeled Kinetics (ours)	**60.33 / 58.47**
Supervised MAML on Kinetics	71.08 / 69.44

CelebA results

Algorithm (N, K)	(5, 1)	(5, 5)	(5, 10)
Training from scratch	26.86	39.65	50.61
UMTRA (ours)	**33.43**	**50.19**	**58.84**
Supervised MAML	72.26	84.90	88.26

Thank you!

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